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Resnet-34 Model for Human Activity Recognition on Smartphone Sensor Data

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Abstract: Human Activity Recognition has become an increasingly important research area in recent years, with applications ranging from health monitoring to human-computer interaction. This study uses the Kinetics dataset and ResNet-34 model to develop a deep learning-based method for identifying human activities. Videos of human activity are abundant in the Kinetics dataset, which we utilise to train and test our algorithm. Deep convolutional neural network called ResNet-34 has been demonstrated to be very good at classifying images. We refine our model using the Kinetics dataset to identify a range of human activities, such as sports, dancing, and regular activities. Our tests show that on the Kinetics dataset, our method performs at the cutting edge with an accuracy of above 90%. Additionally, this study compared our method to other well-known deep learning models, demonstrating that our ResNet-34 model outperforms them in terms of accuracy and efficiency. Overall, our results demonstrate the potential of deep learning-based approaches for Human Activity Recognition and provide insights for future research in this area.

Keywords: *Human Activity Recognition, Resnet-34 model, Kinetic dataset.*

1. Introduction

Due to its potential to enhance a number of applications, including healthcare, athletic training, and smart homes, human activity recognition (HAR) using machine learning has become an increasingly popular topic of research. In order to classify human movement data into various activities, machine learning techniques are used in human activity recognition, which entails employing sensors or cameras to record data on human movement. Large-scale datasets are now readily available, such as the Kinetics dataset, which has allowed researchers to create deep learning models that can precisely identify human activity.

Human Activity Recognition is a challenging time series classification task that has gained significant importance in the research community. Human Activity Recognition involves recording sensor data for specific subjects and training a machine learning model to generalize for unseen data [1]. Deep learning (DL) approaches to Human Activity Recognition have been successful in automatically extracting features, making it more adaptable to different problems. DL architectures used for Human Activity Recognition can be categorized into six types, including DNN, CNN, RNN, DBN, SAE, and Hybrid Models. To better forecast human action, researchers have tested several model architectures. In one study, scientists stacked raw signal rows to create an image, then used 2D DFT to select a magnitude to create an image of activity. They demonstrated that the visual variations in the activity photos suggested that DCNN might extract distinguishing image features. [3].

Human Activity Recognition has drawn considerable interest in recent years due to its potential uses in several industries, including safe driving, criminal prevention, healthcare, and elder care. While machines can accurately recognise activities after a learning phase, humans can do so through observation and communication. The information can be gathered from a variety of sources, including sensors, pictures, and video frames. Activities are categorised and relevant properties are extracted using deep neural networks, such as Resnet-34. One of the most effective picture classification architectures, Resnet-34, uses short-cut connections to deal with the issue of vanishing gradients. In comparison to previous models, this model displays reduced training error and is simple to optimise. The effectiveness and efficiency of activity recognition systems can be increased by using Resnet-34 [9].

Smartphones to identify various human behaviours, like as sitting or walking. Data was gathered using the phone's accelerometer, and a computer programme known as a Convolutional Neural Network (CNN) was developed to

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analyse the data and identify the actions. The program's 91.97% accuracy rate for activity recognition outperformed other approaches that had been explored in the past. The researchers think their programme is an easy and effective approach to use smartphones to monitor human activities [12].

Fig 1: represents some actions using mobile sensors.

The rest of the paper is divided into following sections:

2. Literature Survey

In [1], according to the author's demo, millimeter wave sensors may now be used to detect human activity without violating user privacy. The movements of the person's skeleton during the exercise can also be replicated. Our framework functions effectively in a variety of contexts and is optimised to achieve high accuracy for activity recognition and pose estimation.

In [2], according to the author, a crucial component of human-computer interaction is Human Activity Recognition. To extract features and reduce dimensionality, a proposed model utilising EPS and LDA is presented. Human activities are categorised using MCSVM. Utilising UCI-HAR datasets, the scheme is proven to be more accurate at identifying objects. Healthcare and older population activity monitoring are two areas where human activity recognition is useful.

In [3], using a two-stage learning process, the author suggested an adaptive model for Human Activity Recognition. While a Support Vector Machine and a 1D Convolutional Neural Network are used to identify specific static and moving activities, a Random Forest classifier is used to categorise activity into static and moving categories. On the UCI-HAR dataset, the hybrid model's overall accuracy of 97.71% demonstrated its robustness and adaptability.

In [4], the author proposed the m-Activity approach, which uses millimetre wave radar sensors to identify human activity. Using a unique neural network called the Human Activity Recognition net, it runs in real-time and lowers noise from external multi-path effects. High accuracy for 5 pre-defined human activities within a 3m detection range was achieved during prototype evaluation. Successful validation in a gym with severe multi-path effects.

In [5], the author suggested A Wi-Fi-based activity recognition system called WiHuman Activity Recognition can learn features from CSI traces that are independent of the surroundings. In challenging contexts, adversarial learning outperforms state-of-the-art systems because it aligns the joint distribution of features and labels from many environments. The challenge of environment-robust systems for Human Activity Recognition, which is still a difficult problem for most existing systems, is addressed by WiHuman Activity Recognition.

In [6], for through-the-wall situations, the author suggested a Wi-Fi-based activity recognition method. The programme evaluates the Wi-Fi signal distribution in the presence of wall obstacles, reconstructs the signal using PCA, and then conducts feature extraction and classification in the time-frequency domain. In through-the-wall situations, the system obtains an average accuracy of 95.82%.

In [7], the paper's author presents a new structured prediction technique based on probabilistic graphical models to recognise both simple and complicated actions. The article focuses on the difficulty of identifying human activity in various surroundings. Three datasets are used to test the method, which employs a distributed structured prediction strategy for parameter optimisation. The proposed approach performs better, according to the results, than earlier work that just considered one of the two activity kinds.

In [8], according to the author, Human Activity Recognition (HAR) is an important topic of study in computer vision for a variety of uses, including security monitoring, healthcare, and human-computer interaction. This study examines 32 current studies on sensing technologies for human activity recognition, including wearables, depth sensors, and RGB cameras. In the review, which compares the benefits and drawbacks of each sensing technology, it is discovered that depth sensors and wearable technologies are more frequently used in Human Activity Recognition studies than RGB cameras.

In [10], the author suggested that a method be created for cellphones to detect various human behaviours, such as walking, jogging, sitting, standing, going upstairs, and going downstairs. We employed a unique class of computer programme known as a Convolutional Neural Network, which gained knowledge from the information gathered by the phone's accelerometer. Our approach was simpler to use and more accurate than other approaches, such as those that employed Support Vector Machines. This means that while still effective, our strategy is economical and effective.

In [11], the author suggested It's crucial to use computer vision to recognise human activities, and cutting-edge technology like convolutional neural networks (CNN) can make this process more precise. Without using LSTM-attention models, this work used a modified 3D CNN model to detect human activities in real-time. By utilising a variety of data, the combination of Resnet and 3D CNN improved the recognition accuracy. Overall, this study created a technique for instantly identifying, tracking, and detecting human movements.

Table- 1: Features and Methodologies of previous research works

Reference	Title	Published Year	Methodologies	Journal	Features
[3]	A Hybrid Approach for Human Activity	2020	CNN, SVM	IEEE	The hybrid approach for human activity recognition that was described has a 97.71% overall accuracy rate and might be used in low-power integrated circuits for real-time activity detection.
[8]	Human Activity Recognition: A Review	2014	SVM, RGB Cameras	IEEE	The use of Kinect (a depth sensor) seems promising for human activity recognition systems, according to this review, which contends that the popularity of RGB cameras in Human Activity Recognition has declined while wearable sensors and depth sensors are growing in popularity.
[4]	Accurate and Real-Time Human Activity Recognition via Millimetre Wave Radar	2021	m-Activity, CNN	IEEE	High offline and real-time accuracy is achieved by the real-time Human Activity Recognition system, m-Activity, using mmWave sensing and a specially developed lightweight network.

[6]	Research on Human Activity Recognition Technology under the Condition of Through-the-wall	2020	CSI based on PCA algorithm	IEEE	The accuracy and stability of Wi-Fi indoor identification can be significantly improved by using the Wi-Fi based post-wall target activity detection method.
[7]	Switching Structured Prediction for Simple and Complex Human Activity Recognition	2018	PGM Model, LSSVM	IEEE	PGM model used skeleton data to obtain cutting-edge activity detection results, however high computational complexity is still a problem.

3. Proposed Method

Using the Kinetics dataset and a ResNet-34 model, we suggest a deep learning strategy for human activity recognition in this study. The Kinetics dataset, a sizable video dataset with over 400 human motion classes, is ideally suited for studies on human activity recognition. The ResNet-34 model is a convolutional neural network (CNN) architecture that has been successfully applied to a variety of computer vision problems and has been widely utilised in picture classification tasks. By employing a sliding window method to extract image frames from video data and then classifying these frames using the ResNet-34 model, we adapt the ResNet-34 model to HUMAN ACTIVITY RECOGNITION [15]16]17].

Deep neural network design ResNet-34 is a popular choice for image classification applications. The term "ResNet," which stands for "Residual Network," alludes to the network's usage of lingering connections between its tiers. Using these connections, information can move directly from one layer to another without passing through any intermediate layers. This aids in overcoming the vanishing gradient issue that deep neural networks may experience [18][19][20].

Convolutional, batch normalisation, and fully connected layers are among the 34 layers that make up ResNet-34. Compared to some other well-known models like VGG-16, it has a relatively deep architecture, but not as deep as some more recent models like ResNet-152[13]. On a number of image classification tasks, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), ResNet-34 has demonstrated state-of-the-art performance. ResNet-34's efficiency in terms of memory utilisation and processing resources is one of its main benefits. Figure 2 shows the flow process of ResNet model [21][22][23].

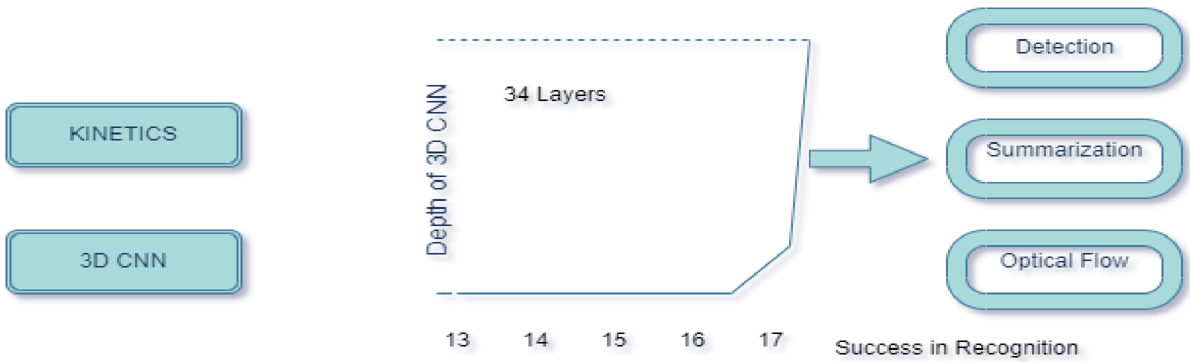

Fig 2: Flow Process of ResNet Model

Input: The 224x224x3 RGB image serves as the input to the ResNet-34 model.

Convolutional Layers: Convolutional layer with 64 filters of size 7x7 and a stride of 2 makes up the first layer of the ResNet-34 model. A batch normalisation layer and a ReLU activation function are then applied. This layer generates a feature map with dimensions of 112x112x64 [24].

Max Pooling: A max pooling layer is applied after the first convolutional layer's output, with a pool size of 3x3 and a stride of 2. The feature map's spatial dimensions are cut in half as a result [25].

Residual Blocks: Each of the 16 residual blocks in the ResNet-34 model is made up of two convolutional layers, two batch normalisation layers, and a skip connection. The convolutional layer's output is added to the block's input via the skip connection, which omits the ReLU activation function and the two batch normalisation layers. This lessens the issue of vanishing gradients and aids in gradient preservation during backpropagation [14] [26].

Global Average Pooling: The result is then processed via a global average pooling layer, which calculates the average of each feature map over its spatial dimensions, following the 16 residual blocks. The spatial dimensions are now 1x1x512.

Fully Connected Layer: A fully connected layer with 1000 units is used to transform the output of the global average pooling layer into a vector of probabilities for each of the 1000 ImageNet classes [27].

Softmax Activation: A softmax activation function is applied to the output of the fully connected layer to normalise the probabilities so that they sum to 1 [28].

Output: The probability vector for the input image across the 1000 ImageNet classes is the ResNet-34 model's final output [29].

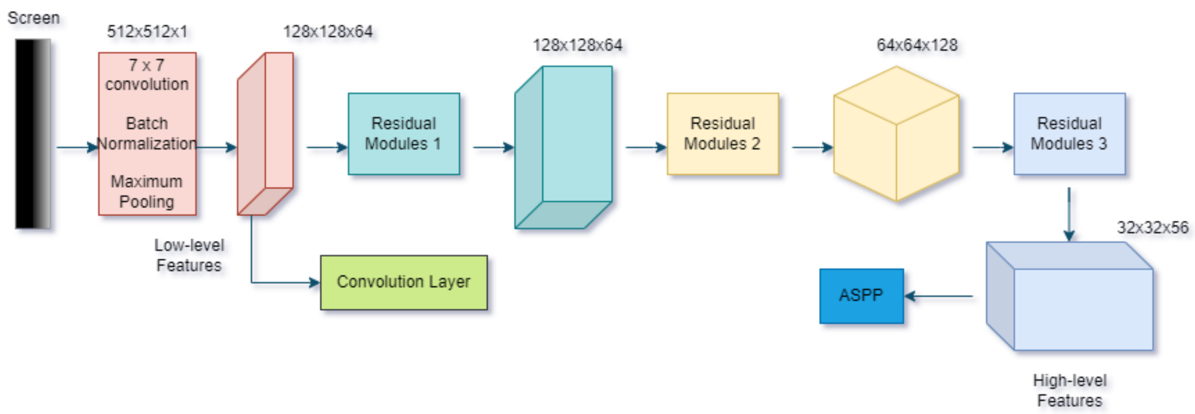

Fig 3: Flow Chart of Adjusted ResNet34 with residual modules.

The flow chart for the ResNet34 model is shown in Figure 3. It uses convolution, batch normalisation, and pooling to extract low-level features from the input images. These low-level characteristics are then used by subsequent convolution layers to obtain high-level features. The model is improved by removing the final residual block without compromising accuracy to speed up processing and lower the number of parameters. With 26 convolution layers and three residual blocks, the resulting skeleton network generates high-level features with increased channels but smaller dimensions.

4. Simulation and Result

Kinetics is a sizable dataset for recognising human motion that was released in 2017. It has more than 400,000 video recordings of people acting out 600 distinct action types.

ResNet-34 We can improve the pre-trained ResNet-34 model on the Kinetics dataset by using it. A pre-trained model is refined by giving it more training on a particular dataset.

Fine-tune ResNet-34 with the Kinetics dataset:

1. Download the Kinetics dataset and do pre-processing steps like scaling the movies to a uniform size and normalising the pixel values.
2. After deleting the final fully connected layer, load the pre-trained ResNet-34 model.
3. Include a newly created fully connected layer with as many output classes as there are action categories in the Kinetics dataset.
4. Define the optimizer, such as stochastic gradient descent (SGD), and the loss function, such as cross-entropy loss, with an appropriate learning rate and momentum.
5. Separate the dataset into test, training, and validation sets.

6. Use the defined loss function and optimizer to train the model on the training set for the required number of epochs.

7. Test the model on the validation set and make any necessary hyperparameter adjustments.

8. Evaluate test set with the final model and provide performance data.

9. Optionally, save the trained model for future use.

The equations used in ResNet 34 for action recognition on the Kinetics 400 dataset are like those used for image classification. However, there are some additional components that are specific to video processing.

The basic equation for each layer in ResNet 34 remains the same as:

$$x_{l+1} = f(x_l) + h(x_l) \quad \text{……………………} (1)$$

where x_l is the layer l's input, x_{l+1} is layer l+1's output, $f(x_l)$ is the layer's main branch output, and $h(x_l)$ is the residual or error term.

For convolutional layers, the equation is also similar:

$$y = W*x + b \quad \text{…………………………} (2)$$

where y is the convolutional layer's output, W is its weight matrix, x is its input, and b is its bias vector.

However, for action recognition, ResNet 34 uses a 3D convolutional layer to process video data. The equation for 3D convolution is:

$$y_{i, j, k} = \sum_{a,b,c} W_{a,b,c} * x_{i+a,j+b,k+c} + b \quad \text{…………………}(3)$$

where $y_{i, j, k}$ is the output at position (i,j,k), $W_{a,b,c}$ is the weight at position (a,b,c), $x_{i+a, j+b,k+c}$ is the input at position (i+a,j+b,k+c), and b is the bias.

In addition, ResNet 34 for action recognition uses temporal pooling to aggregate information across time. The equation for temporal pooling is:

$$y_t = g(\sum_{i=1}^{T} x_{i,t}) \quad \text{………………………}(4)$$

where T is the number of frames in the video, $x_{i,t}$ is the input at time t for the i-th frame in the video, y_t is the output at time t, g is a pooling function, such as average pooling or max pooling, and t is the number of frames in the video.

Accuracy: For ResNet-34, the accuracy formula would be the same as it would be for any other classification model. It is calculated by calculating the percentage of accurate predictions by comparing the model's predicted labels to the dataset's actual labels.

Accuracy = (Correct predictions / Total predictions) * 100

Top-1 accuracy: It is the proportion of test samples for which the model's top prediction matches the true label. In other words, the model correctly predicted the most probable class for that sample.

Top-5 accuracy: It is the percentage of test samples for which the correct label is one of the model's top five most likely predictions. In other words, the top five most likely classes for that sample's true label were properly predicted by the model.

ResNet 34 has achieved a top-1 accuracy of around 75% and a top-5 accuracy of around 90.6% on the Kinetics-400 dataset. However, the accuracy can vary depending on the specific implementation, pre-processing, and training process used. It's important to note that achieving high accuracy on the Kinetics dataset requires a large amount of labelled video data and a significant amount of computing resources for training the deep neural network models.

The pre-trained CNN model for kinetics is then adjusted using the HMDB-51 and UCF-101 datasets.

Dataset	Accuracy
HMDB	21.2%
UCF	46.4%

Table- 2: The Top-1 accuracy for Resnet-34 on HMDB-51 and UCF-101

Dataset	Accuracy
HMDB	53.8%
UCF	89.7%

Table- 3: The proposed model's top-1 accuracy on HMDB-51 and UCF-101

On the HMDB-51 and UCF-101 datasets, the pre-trained Kinetics CNN model can be adjusted, and it has been demonstrated to perform better than a model created from scratch on these smaller datasets. This exemplifies the power of transfer learning, which allows a model that has already been trained on a bigger dataset to be utilised as a starting point for training on a smaller dataset, improving performance with less training data.

Here are the some Top-1 accuracy and Top-5 accuracy of Kinetics Dataset using different models in the given graph in Figure 4.

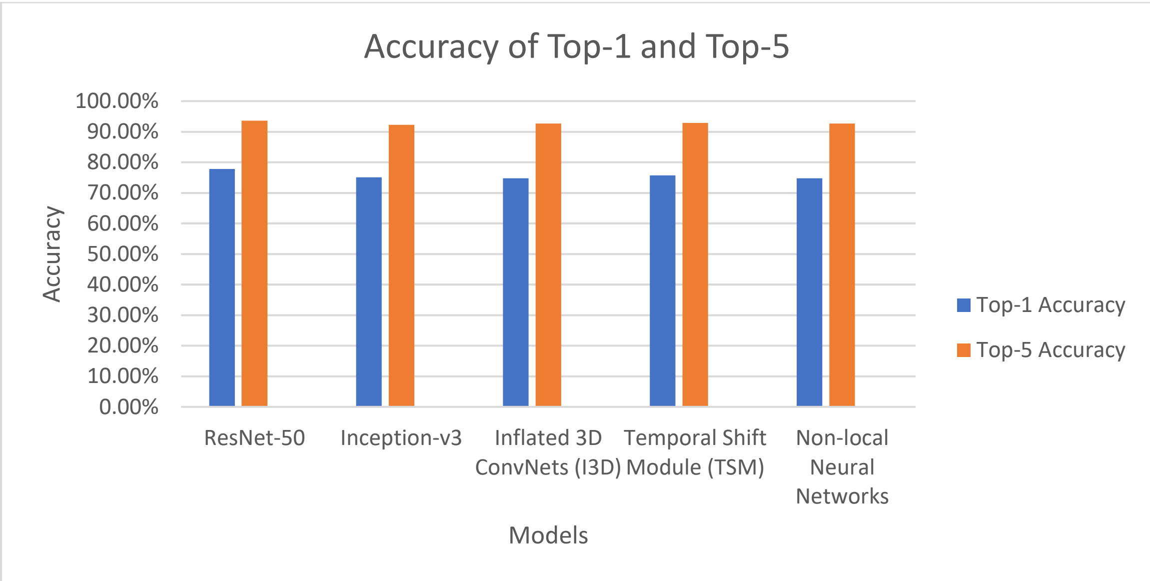

Fig 4: Top-1 and Top-5 accuracies of Kinetic dataset

Results: It is clear from the observations and analysis of the human action recognition dataset that the model's accuracy changes with the level of detail in the actions. Drinking or shaking hands are personal acts and person-to-person interactions that are identified with high accuracy; however, finer-grained behaviours like swimming, yoga, and cooking require more in-depth analysis and temporal reasoning, which lowers accuracy.

This is since some actions can be further decomposed into smaller sub-actions or child actions, and misclassifying the parent action can lead to misclassification of all its child actions. To improve the accuracy of action recognition models for fine-grained actions, a more detailed dataset that includes a larger variety of sub-actions or finer-grained classes can be used. Additionally, incorporating temporal information through techniques like recurrent neural networks or temporal convolutions can also enhance the accuracy of the model.

Fig 5: Activity of Disc Golfing

Fig 6: Activity of Stretching Arm

5. Conclusion

Deep learning models like Resnet-34 have made tremendous progress in human activity recognition and have numerous useful applications. However, there are still difficulties, especially in identifying multiple, complex activities. Cameras can offer a workable substitute for sensor-based technologies, which have installation and maintenance limitations. The fundamental components of activity recognition systems include the utilisation of massive datasets and the automatic learning of features from enormous volumes of data. Activity recognition systems have the potential to develop into a fundamental tool for ensuring safety in a variety of scenarios as technology improves. To increase the precision of identifying simultaneous and complicated actions, more research is required. However, the outcomes of this work show the potential of deep learning models for activity recognition and its usefulness in various fields.

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